Heterogeneous Computational Resource Allocation for C-RAN: A Contract-Theoretic Approach

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Abstract—In this work, we develop a contract theory framework to tackle the allocations of heterogeneous baseband processing units (BBUs) in cloud radio access network. We first model a monopoly market by viewing the BBUs as a kind of resource. The infrastructure provider (InP), as the monopolist, owns all the heterogeneous BBUs of different processing abilities and maintaining costs, and leases them to multiple mobile network operators (MNOs) to gain profit. At the same time, the MNOs intend to rent reasonable amount of BBUs to provide services to their mobile clients. Then we propose a contract theory framework, in which contract items are optimized to maximize the InP's utility, while maintain the welfare of the MNOs. We design the optimal contracts with complete and asymmetric information on the MNOs. Our contract design achieves the near optimum solution to heterogeneous computational resource allocation even under the information asymmetric case. Our derivations indicate that the optimal contracts with asymmetric information achieve a lower utility for the InP than the ones with complete information and the utility reduction is higher when the BBUs are heterogeneous rather than homogeneous. Numerical results demonstrate that, the InP having heterogeneous BBUs can achieve a higher utility relative to having homogeneous BBUs, which is more profitable and realistic for the InP. Moreover, we regard Stackelberg game theoretic approach as a comparison, and show that our method is more realistic.

Index Terms—Heterogeneous computational resources allocation, virtualized base station, cloud-RAN, cellular networks, contract theory, incentive mechanism

1 Introduction

Nowadays, ubiquitous mobile devices and ever-increasing individual demands for data rate have led to the overloaded traffic in cellular networks. In general, the overloading issues are commonly alleviated by increasing bandwidths or densifying base stations (BSs). However, considering the consequent high cost and low resource utilization efficiency, these solutions may not be feasible in a traditional radio access network (RAN), where the BSs are normally isolated with limited cooperation among them. Thus, the cloud/centralized RAN (C-RAN) has been proposed to tackle the overloading issues efficiently by centralizing computational resource into a pool and virtualize them on demand [1–4], where computational resource is usually referred to as baseband processing unit (BBU). The BBU resource in C-RAN can be allocated to mobile network operators (MNOs) virtually to provide services to mobile clients and the virtualized BBU resource is termed as virtualized base station (VBS). We note that, in order to optimize the BBU resource utilization, BBU resource allocation problems have become very important in C-RAN, and there are many related works in this area (e.g., [5–8]). In [5], the authors proposed a BBU virtualization scheme that minimized the power consumption, which was based on a heuristic simulated annealing algorithm. In [7], in order to maximize the utility for the links between users and transmitters, the authors formulated virtual resource allocation and caching optimization as a discrete stochastic optimization problem and tackled the problem by using discrete stochastic approximation approaches.

However, the above mentioned works usually consider homogeneous BBU resource allocation problems, while the newly proposed C-RAN architecture may consist of heterogeneous BBU resources in order to meet various demands of different applications (e.g., live video downloading, online gaming) [9–12]. Different from traditional C-RANs, which allocates BBUs from homogeneous BSs , heterogeneous C-RANs can serve customers with BBUs from heterogeneous BSs with diverse BBUs (e.g., pico BS, femto BS, macro BS) [13–17]. As a result, heterogeneous C-RANs are realistic since an InP usually has BBUs with different computing power. Moreover, heterogeneous C-RANs can meet various requirements for computing power effectively by providing heterogeneous BBUs rather than adjusting the number of homogeneous BBUs. In wireless networks, when it comes to heterogeneous resource allocation, it mainly points to heterogeneous radio resource allocation rather than

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heterogeneous BBU resource allocation. Thus, there are lots of works involving heterogeneous radio resource allocation problems [18–20], while very few works are about allocating heterogeneous BBU resources. In [18], a truthful double auction mechanism for channels with spatial and frequency heterogeneity was proposed to allocate channels to multiple secondary service providers. A similar mechanism was considered in [19], where the discussed heterogeneity of channels is different from that considered in [18]. The model was based on auction design, where a primary spectrum owner sold some idle channels to multiple secondary users with the highest valuations. In [20], the authors used game theory to solve the problems of heterogeneous spectrum resource allocation and pricing. In this model, several secondary users (SUs) purchase the channels with different center frequencies from two wireless service providers (WSPs) to maximize SUs' own utility.

Meanwhile, contract theory has been widely adopted to optimize resource allocation in wireless communications recently (e.g., [21–27]), which is a mature approach from economics to design an effective incentive mechanism and it enables the monopolist to achieve the maximal utility by designing proper quantity-price contract items for consumers for certain goods, while stimulating the consumers to accept the designed contracts. For example, the work [22] adopted contract theory to motivate content providers to rent small-cell base stations from a network service provider, where derivation is used to obtain the optimal contracts. In addition, it compared the contract scheme with other schemes (e.g., uniform quality scheme and Stackelberg game scheme). In [23] the authors designed a set of optimal contracts to select relays under asymmetric information in OFDM cooperative wireless networks. Although a very few works adopted the contract theory to tackle the heterogeneous resource allocation problem (e.g., [23]), the work did not provide a closed-form solution to this problem. In addition, some interesting problems in the context of heterogeneous resource allocation are still open and deserve further research efforts. For example, how to allocate heterogeneous BBU resource optimally, and what is the benefit of having heterogeneous BBU resource relative to having homogeneous BBU resource? Deriving a closed-form solution to the optimal heterogeneous resource allocation problem in C-RANs and tackling the related important questions mainly motivate this work.

In this paper, we develop a novel contract theoretic framework to tackle the heterogeneous BBU resources allocation problem between the InP and multiple MNOs for C-RAN. The heterogeneity of BBUs (i.e., power consumption and processing ability) leads to the varying preference of the MNOs, which further results in diverse desired trading quantities and acceptable prices. New challenges in designing the contracts are how to use the contract theory to allocate the heterogeneous BBU resources, and how to obtain the closed-form solutions of the optimal contracts, since the optimal function and some of the derivation and proof procedures of contract theory have changed compared to allocating homogeneous resource.

The main contributions of this work are summarized as follows.

- We propose a novel contract theoretic framework to tackle the heterogeneous BBU resources allocation problem in C-RANs, where we design a set of quantity-price contract items for maximizing the InP's utility with multiple rational MNOs by stimulating each MNO to accept the contract item that is intently designed for it.
- We design the optimal contracts when the InP does not know exactly about MNOs' preference to BBUs. In order to obtain the true preference of the MNOs and ensure that they accept the designed contracts, two extra constraints, i.e., incentive compatible (IC) and individually rational (IR) constraints, are considered when we design the contracts. We derive the closed-form solution of the optimal contracts, which is based on Lagrangian multipliers and Karush-Kuhn-Tucker (KKT) conditions. As a result, the utility at the MNO with the lowest preference is guaranteed to its reservation utility which is the least utility each MNO can accept to participate in the trade.
- We provide the method to obtain the explicit solutions to the optimal contracts design when the InP knows exactly about MNOs' preference to BBUs, and regard this case as a benchmark.
- Although having heterogeneous BBUs can increase InP's utility relative to having the same amount of homogeneous BBUs, our examination demonstrates that, in order to obtain the true preference of MNOs, the InP has to sacrifice some utility, and this sacrificed utility at the InP is higher for heterogeneous BBUs than that for homogeneous BBUs.

The rest of this paper is organized as follows. Section 3 details the system model for heterogeneous BBUs allocation in C-RANs. In Section 4 and Section 5, we present the optimal contract designs without and with knowing exactly about MNOs' preference respectively. In Section 6, we present numerical results and provide many useful insights on the heterogeneous BBU resources allocation in C-RANs. Finally, we draw conclusions in Section 7.

2 Related Work

2.1 Heterogeneous Cloud Radio Access Networks

Recently, heterogeneous C-RANs have attracted intense interest from both academia and industry [13, 28, 29]. In [13], authors proposed the concept of heterogeneous C-RANs, and outlined technological features and core principles behind heterogeneous C-RANs. In [28], a contract-based interference coordination framework in heterogeneous C-RANs was proposed to mitigate the inter-tier interference between remote radio heads (RRHs) and macro base stations. In [29], authors addressed the problem of cooperative radio resource management in heterogeneous C-RANs by providing a comprehensive mathematical methodology for its realtime performance optimization. However, a few works are about heterogeneous computing resource allocation in heterogeneous C-RANs.

2.2 Contract Theory

Another important issue to emphasize is contract theory. Contract theory can provide participation incentive for both parties to a transaction, while involving statistical information about buyers. As a result, sellers can make pricing efficiently, leading to a wide application of contact theory in resource allocation [30–32]. In [30], a monopolist-dominated quality-price contract was designed to achieve efficient spectrum trading. Then, they proposed the necessary and sufficient conditions for the contract to be feasible, and derived the optimal contract. The work [31] adopted contract theory to motivate mobile users to leverage their delay tolerance in exchange for the service cost in the delayed traffic offloading scheme. As a result, operator's profit for both the continuous-user type model and the discrete-user-type model was maximized. In [32], authors used contract theory to study the problem of joint user association and intercell interference mitigation in heterogeneous long-term evolution advanced networks, and exploited the OPNET based simulations to evaluate the performance of the proposed contract-based resource allocation mechanism. However, the above mentioned works usually consider homogeneous resource allocation problems, which means the price of resource is only relative to the amount rather than the difference among resource. Moreover, there are few works considering heterogeneous resource allocation problems, but they failed to obtain closed-form solutions.

3 System Model

In this section, we detail the considered system model. Specifically, we first present the adopted assumptions, and then provide the InP and MNO models in detail.

3.1 Assumptions

In this work, the BBUs allocation process is represented as a trade in a monopoly market. As a monopolist, the InP owns all the BBUs, and intends to lease them to multiple MNOs in order to gain profit. Meanwhile, the MNOs need to rent BBUs from the InP to provide good quality services to their mobile subscribers. We first assume that the number of BBUs is finite and these BBUs are heterogeneous, while they can be classified into M BBU groups according to their heterogeneity. Specifically, in this work we assume that the power consumption and the processing capabilities of the BBUs in different groups are different. In heterogeneous networks, MNOs may have different radio coverage distances and preference to different BBU groups. The preference is related to the specific services that each MNO provides in the

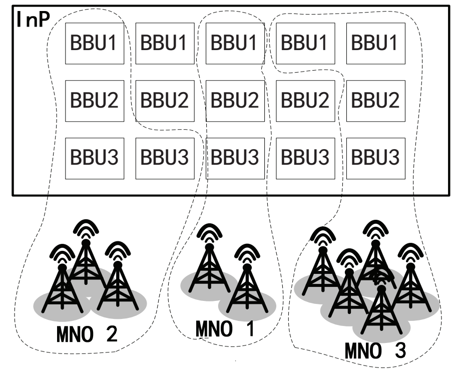

Fig. 1. An example of the BBU trading with 1 InP and 3 MNOs. The InP owns 3 heterogeneous BBUs and leases them to MNOs. The leased units for each BBU kind may be different according to each MNO's demand. The dash line circles each MNO's RRHs and its rented BBUs.

mobile networks, e.g., live video streaming and online gaming. In this work, we assume that these MNOs can be classified into N different types according to their preference to each BBU group.

For each pair of one MNO type and one BBU group, we adopt a parameter $\theta_{mn}, m = 1, \cdots, M; n = 1, \cdots, N$ to determine the benefit gained by MNO type n from BBU group m. We note that for different MNO types or different BBU groups, θ_{mn} is different. In order to maximize its total utility, the InP designs a set of contracts to allocate the BBUs to the MNOs. Specifically, the InP has to determine a matrix $\mathbf{P} = \{p_{mn}\}$, where p_{mn} denotes the fraction of the m-th group BBUs allocated to the n-th MNO type, $p_{mn} \in [0, 1]$ and $\sum_{n=1}^{N} p_{mn} \leq 1$. For renting p_{mn} BBUs, the MNO should pay expense $\varepsilon_{mn}(p_{mn})$ to the InP. Let $\mathbf{E}$ denote the matrix of the renting expenses ε_{mn}.

To obtain the maximal utility, the InP has to determine the allocation fraction matrix $\mathbf{P}$ and the corresponding price matrix $\mathbf{E}$ in the design of different contracts.

3.2 InP Model

In this subsection, we detail the adopted InP model, in order to obtain the InP's utility which is our objective function. Specifically, the utility, which can be achieved by the InP through renting BBUs from group m to the n-th type of MNOs, is given by [30]

$$U_I(\theta_{mn}, p_{mn}) = (w_1 G(\varepsilon_{mn}) - w_2 C(p_{mn})) \mathbf{l}_{p_{mn}>0}, \quad (1)$$

where $G(\varepsilon_{mn})$ means the InP's satisfaction of the price ε_{mn} and $C(p_{mn})$ denotes the cost of operating BBU p_{mn}. $w_1 > 0$ and $w_2 > 0$ are the efficiencies of the conversion from satisfaction to utility and the conversion from cost to utility, respectively. In addition, $\mathbf{l}_{p_{mn}>0}$ is an indicative function. That is, if $p_{mn} > 0$, then $\mathbf{l}_{p_{mn}>0} = 1$, otherwise $\mathbf{l}_{p_{mn}>0} = 0$.

Intuitively, $G(\varepsilon_{mn})$ is monotonically increasing with ε_{mn}. When the price approaches zero, $G(\varepsilon_{mn})$ will approach a minimal value, i.e., $G_0 = \lim_{\varepsilon_{mn}\to 0} G(\varepsilon_{mn})$. If the price increases to infinity, the InP's satisfaction of the price will approach infinity as well, i.e.,

$\lim_{\varepsilon_{mn}\to\infty} G(\varepsilon_{mn}) = \infty$. Inspired by the above analysis, we model the InP's satisfaction as the exponential form and adopt the logarithm function as well, which is generally used in the economic literatures [31], i.e., $G(\varepsilon_{mn}) = \ln(G_0 e^{\alpha\varepsilon_{mn}}) = \ln G_0 + \alpha\varepsilon_{mn}$. Here α is a positive adjusting parameter.

We define the operating cost as $C(p_{mn}) = a \cdot t(p_{mn})$, where $t(p_{mn})$ is the power consumption and a is a positive conversion ratio. We regard the power consumption as the main factor in the operating cost since the fact that electricity has accounted for more than one-half of total operating spending [2]. Moreover, the reason for proposing C-RAN is to improve energy efficiency, and thus power consumption is the main concern in C-RANs. Specifically, if the InP allocates p_{mn} BBUs resources to the MNO with θ_{mn} which is the benefit gained by the MNO from BBU group m, the corresponding power consumption can be expressed as $t(p_{mn}) = p_{mn} H_m c_m$, where H_m is the total number of BBUs in the m-th BBU group, $p_{mn}H_m$ denotes the number of active BBUs in the mth BBU group, and c_m is each BBU's power consumption which is in inverse proportion of θ_{mn}. Following [33], we assume that $c_m = (\frac{k_m s_0}{\theta_{mn}})^\beta$, where s_0 is the reference BBU processing ability, $k_m s_0$ is the processing ability of the BBUs in the m-th BBU group, and β is the exponential coefficient of the BBU processing ability. In general, $C(p_{mn})$ is a monotonically increasing function of p_{mn}, which means that if more BBUs are allocated, the corresponding cost is higher.

Without loss of generality, we assume $\ln G_0 = 0$ and $\alpha = w_1 = w_2 = 1$. In addition, if $p_{mn} = 0$, which means no BBU is allocated to the MNO with θ_{mn}, we have $C(p_{mn}) = G(\varepsilon_{mn}) = 0$. Then, following (1), the InP's total utility can be obtained by adding up $U_I(\theta_{mn}, p_{mn})$ for all the values of m and n.

3.3 MNO Model

In this work, we assume that each MNO uses the parallel computing method to process its tasks in order to improve its performance [34–36]. This means that the task of one MNO can be processed by many BBUs in different groups simultaneously. Then, we adopt the Amdahl's law [37, 38] to depict the maximum improvement achieved by deploying parallel computing, i.e., $M(p_{mn}) = \frac{1}{\eta + \frac{1-\eta}{p_{mn}H_m}}$, where η is the proportion of the task that can only be conducted serially. Note that Amdahl's law provides a theoretical upper bound for the improve of the execution time of applications run in parallel. But there are other issues (e.g., communications, deadlocks, syncs) that can reduce the improvement achieved. In this work, we just consider the ideal situation with parallel applications for simplification. Following $M(p_{mn})$, the benefit gained by the MNO with θ_{mn} from the BBU group m is given by

$$B_O(\theta_{mn}, p_{mn}) = \theta_{mn} M(p_{mn}) = \theta_{mn} \frac{1}{\eta + \frac{1-\eta}{p_{mn}H_m}}. \quad (2)$$

We note that $B_O(\theta_{mn}, p_{mn})$ monotonically increases with p_{mn} and θ_{mn} due to $0 \le p_{mn} \le 1$ and $0 \le \eta \le 1$. Then, for the MNO with θ_{mn}, the utility of renting p_{mn} BBUs can be expressed as

$$U_O(\theta_{mn}, p_{mn}) = B_O(\theta_{mn}, p_{mn}) - \varepsilon_{mn}. \quad (3)$$

In this paper, we will discuss complete and asymmetric information in the next two sections, respectively.

4 Contract Design With Asymmetric Information

In this section, we discuss the optimal contract design in the scenario with asymmetric information [39], where the MNO type θ_{mn} is considered as private information and trade secret for a certain MNO. As such, in this scenario the contracts should be designed subject to two extra constraints according to contract theory, which will be detailed in this section.

4.1 Optimization Problem and Its Simplification

In this section, we consider a practical assumption on θ_{mn}, where the MNO type for the m-th BBU group denoted by θ_m, follows a discrete uniform distribution, i.e., θ_{mn} for all possible values of n are drawn from a discrete uniform distribution. Specifically, we have

$$\theta_{mn} = \theta_{m1} + \frac{(n-1)(\theta_{mN} - \theta_{m1})}{N-1}, n = 1, 2, \ldots, N, \quad (4)$$

where θ_{m1} and θ_{mN} are the lower and upper bounds on θ_{mn} and $\theta_{m1} < \theta_{mN}$. As per (4), we note that the benefit gained by MNO type n from BBU group m increases with the growth of n. Thus, MNO type n for each BBU group can represent the preference of the MNO to the BBU group, and each MNO has different n for different BBU groups.

Given the distribution of MNO type θ_{mn} and the utility obtained from each MNO type, the InP's total utility can be written as

$$U_I = \sum_{m=1}^{M} \sum_{n=1}^{N} \left(\varepsilon_{mn} - C(p_{mn})\right) \rho_{mn} \mathbf{1}_{p_{mn}>0}, \quad (5)$$

where ρ_{mn} is the probability that an MNO is associated with θ_{mn}. In this work, we have $\rho_{mn} = 1/N$ for the discrete uniformly distributed θ_m.

In this section, θ_{mn} should be reported by each MNO since it is private information. However, in order to obtain higher utility, θ_{mn} reported by each MNO may not be true, although it is available at the InP in the design with asymmetric information. As such, the InP has to consider two extra constraints to make all MNOs accept the contracts designed for their true θ_{mn}.

The first constraint is the incentive compatible (IC) constraint, which is given by $U_O(\theta_{mn}, p_{mn}) \ge U_O(\theta_{mn}, \hat{p}_{mn})$, where $U_O(\theta_{mn}, \hat{p}_{mn})$ is the utility achieved by the MNO through reporting $\hat{\theta}_{mn}$ instead of θ_{mn}, which is given by

$$\begin{aligned} U_O(\theta_{mn}, \hat{p}_{mn}) &= \left(B_O(\theta_{mn}, \hat{p}_{mn}) - \hat{\varepsilon}_{mn}\right) \mathbf{1}_{\hat{p}_{mn}>0} \\ &= \left(\theta_{mn} M(\hat{p}_{mn}) - \hat{\varepsilon}_{mn}\right) \mathbf{1}_{\hat{p}_{mn}>0} \end{aligned} \quad (6)$$

$$= \left(\theta_{mn}\frac{1}{\eta+\frac{1-\eta}{\hat{p}_{mn}H_m}} - \hat{\varepsilon}_{mn}\right)\mathbf{1}_{\hat{p}_{mn}>0},$$

while $\hat{p}_{mn}$ and $\hat{\varepsilon}_{mn}$ denote the allocated BBU fraction and the associated price of the dishonest MNO, respectively. We note that $\hat{p}_{mn}$ and $\hat{\varepsilon}_{mn}$ are determined by the InP based on $\hat{\theta}_{mn}$, where $\hat{\theta}_{mn}$ is dishonestly reported. In (6), $U_O(\theta_{mn}, \hat{p}_{mn})$ is not a function of $\hat{\theta}_{mn}$, due to the fact that the true benefit obtained by the MNO still depends on the true θ_{mn}. The IC constraint guarantees that an MNO can achieve a higher utility by reporting the true θ_{mn} rather than $\hat{\theta}_{mn}$, which ensures that the contract designed based on θ_{mn} is acceptable. We note that the IC constraint is not suitable for further analysis, and thus we simplify it with the following lemma.

***Lemma** 1:* The IC constraint can be replaced by $p_{m1} \leq p_{m2} \leq \cdots \leq p_{mN},\ U_O\left(\theta_{mi}, p_{mi}\right) = U_O\left(\theta_{mi}, p_{m,i-1}\right)$.

Proof: The detailed proof is presented in Appendix A. Using the simplifications in Lemma 2, we can guarantee the truth of θ_{mn} announced by MNOs.

The second extra constraint, which should be considered in the contract design with asymmetric information, is the individual rational (IR) constraint, given by $U_O\left(\theta_{mn}, p_{mn}\right) = B_O\left(\theta_{mn}, p_{mn}\right) - \varepsilon_{mn} \geq 0$, and is achieved based on the assumption that each MNO's reservation utility is zero. This constraint guarantees a nonnegative utility for each MNO, which aims to attract the MNO with θ_{mn} to rent BBUs from the m-th BBU group, and thus enables the MNO to accept the designed contract. Again, we apply the following lemma to simplify the IR constraint instead of using it directly in the design at the InP, since the IR constraint is not easy to handle.

***Lemma** 2:* Assuming the zero MNO's reservation utility if the IC constraint holds, the IR constraint can be simplified as $B_O\left(\theta_{m1}, p_{m1}\right) - \varepsilon_{m1} = 0$.

Proof: The detailed proof is presented in Appendix B. Lemma 2 states that, as long as the MNO with the lowest θ_{mn} accepts the contract designed for it, all other MNOs will accept the contracts designed for them.

In the contract design with asymmetric information, the InP is to design a set of contract items $(p_{mn}, \varepsilon_{mn})$ to maximize U_I while guaranteeing the IR and IC constraints. Therefore, following Lemmas 1 and 2, the optimization problem at the InP in the design can be written as

$$\max_{\mathbf{P},\mathbf{E}} U_I \tag{7a}$$

$$\text{s.t. } p_{m1} \leq p_{m2} \leq \cdots \leq p_{mN}, \tag{7b}$$

$$\sum_{n=1}^{N} p_{mn} \leq 1,\ 0 \leq p_{mn} \leq 1, \tag{7c}$$

$$B_O\left(\theta_{m1}, p_{m1}\right) - \varepsilon_{m1} = 0, \tag{7d}$$

$$U_O\left(\theta_{mi}, p_{mi}\right) = U_O\left(\theta_{mi}, p_{m,i-1}\right), \tag{7e}$$

where the constraint $\sum\limits_{n=1}^{N} p_{mn} \leq 1$ means that BBUs that can be allocated by the InP are limited by the available BBUs and $0 \leq p_{mn} \leq 1$ ensures the reasonable value range of p_{mn}.

We next tackle the above optimization problem. To this end, we first simplify the optimization problem in the following proposition, where we show that $\mathbf{E}$ is determined by $\mathbf{P}$ such that we only have to determine the optimal $\mathbf{P}$ to solve the optimization problem given in (7).

***Proposition** 1:* The optimization problem given in (7) can be rewritten as

$$\max_{\mathbf{P}} \overline{U}_I \tag{8}$$

$$\text{s.t. } 0 \leq p_{mn} \leq 1,\ p_{m1} \leq \cdots \leq p_{mN}, \tag{9}$$

$$\sum_{n=1}^{N} p_{mn} \leq 1,\ \forall m = 1, \cdots, M, \tag{10}$$

where $\overline{U}_I = \sum\limits_{m=1}^{M}\sum\limits_{n=1}^{N}\left(B_O\left(\theta_{mn}, p_{mn}\right) + \triangle_n \Lambda_{mn} - C(p_{mn})\right)\rho_{mn}$, $\Lambda_{mn} = \frac{1-\sum_{i=1}^{n}\rho_{mi}}{\rho_{mn}}$, and $\triangle_n = B_O\left(\theta_{mn}, p_{mn}\right) - B_O\left(\theta_{m,n+1}, p_{mn}\right)$ for $n<N$, $\triangle_n = 0$ for $n = N$.

Proof: Following (7e), we can obtain

$$\varepsilon_{mi} = B_O\left(\theta_{m1}, p_{m1}\right) + \sum_{k=1}^{i} w_k, \tag{11}$$

where for any $i = 1, 2, \cdots, N$, we have $w_k = 0$ for $k = 1$ and $w_k = B_O\left(\theta_{mk}, p_{mk}\right) - B_O\left(\theta_{mk}, p_{m,k-1}\right)$ for $k > 2$. Substituting (11) into (5), the U_I under the constraints given in (7e) can be rewritten as $\overline{U}_I = \sum\limits_{m=1}^{M}\sum\limits_{n=1}^{N}\left(B_O\left(\theta_{m1}, p_{m1}\right) + \sum\limits_{k=1}^{n} w_k - C(p_{mn})\right)\rho_{mn}$, which leads to the desired result in (10). As such, we can replace the objective function U_I with $\overline{U}_I$ in (10) and remove the constraints (7e) in (10), which completes the proof.

Before we detail the steps to solve the optimization problem in (10), we first present the following lemma.

***Lemma** 3:* The InP's total utility $\overline{U}_I$ is a concave function of the BBU allocation matrix $\mathbf{P}$.

Proof: The detailed proof is presented in Appendix C.

Since $\overline{U}_I$ is a concave function of $\mathbf{P}$, (10) is a convex optimization problem [40], which can be solved by convex optimization methods [41,42]. Specifically, we can first write the dual problem of (10), which is equivalent to the optimization problem given in (10) and is easy to solve by adopting the Karush-Kuhn-Tucker (KKT) conditions. The main steps are shown as follows.

Step 1: Obtain the dual problem by the Lagrangian function

The Lagrangian function of the optimization problem given in (10) (exclude the constraint $p_{m1} \leq \cdots \leq p_{mN},\ \forall m = 1, \cdots, M$) can be written as

$$Z\left(\mathbf{P}, \mathbf{U}, \mathbf{L}\right) = -\overline{U}_I - \sum_{m=1}^{M}\sum_{n=1}^{N} \mu_{mn} p_{mn} \tag{12}$$

$$+\sum_{m=1}^{M}\lambda_m\left[\left(\sum_{n=1}^{N}p_{mn}\right)-1\right],$$

where $\mathbf{U}$ and $\mathbf{L}$ denote the Lagrange multipliers of the restriction $p_{mn}\geq 0$ and $\sum_{n=1}^{N}p_{mn}\leq 1$ respectively, which are given by

$$\mathbf{U}=\begin{bmatrix}\cdots & \cdots & \cdots\\ \cdots & \mu_{mn} & \cdots\\ \cdots & \cdots & \cdots\end{bmatrix},\quad \mathbf{L}=\begin{bmatrix}\lambda_1 & 0 & \cdots & 0\\ 0 & \lambda_2 & \cdots & 0\\ \vdots & \vdots & \ddots & \vdots\\ 0 & 0 & \cdots & \lambda_M\end{bmatrix}. \tag{13}$$

According to (12), we can write the dual problem of (10) as

$$\min_{\mathbf{U},\mathbf{L}}\quad Z(\mathbf{P},\mathbf{U},\mathbf{L})\quad \text{s.t.}\quad \mathbf{U}\geq\mathbf{0},\ \mathbf{L}\geq\mathbf{0}. \tag{14}$$

The solution to (14) is same as that to (10), but it is easier to achieve.

Step 2: Introduce the KKT conditions of the optimization problem

Since the optimization problem given in (10) is convex, there is a unique solution $(\mathbf{P}^*,\mathbf{U}^*,\mathbf{L}^*)$ that guarantees the KKT conditions [43] of its dual optimization problem. The KKT conditions are given by

$$\frac{\partial Z}{\partial p^*_{mn}}=-\Bigg(\frac{(\theta_{mn}+(\theta_{mn}-\theta_{m,n+1})\Lambda_{mn})H_m(1-\eta)}{(\eta H_m p^*_{mn}+1-\eta)^2} - ac_mH_m\Bigg)\rho_{mn}-\mu^*_{mn}+\lambda^*_m=0, \tag{15a}$$

$$\mu^*_{mn}\geq 0, \tag{15b}$$

$$\mu^*_{mn}p^*_{mn}=0, \tag{15c}$$

$$\lambda^*_m\geq 0, \tag{15d}$$

$$\mathbf{L}^*\cdot(\mathbf{P}^*\cdot\mathbf{1_N}-\mathbf{1_M})=\mathbf{0}, \tag{15e}$$

where $\mathbf{1_N}$ and $\mathbf{1_M}$ are $N\times 1$ and $N\times 1$ matrixes, respectively, whose elements are all ones.

Step 3: Obtain the closed-form solution from the KKT conditons

Following (15a) and (15b), we have

$$\mu^*_{mn}=-\Bigg(\frac{(\theta_{mn}+(\theta_{mn}-\theta_{m,n+1})\Lambda_{mn})H_m(1-\eta)}{\left(\eta H_m p^*_{mn}+1-\eta\right)^2} - ac_mH_m\Bigg)\rho_{mn}+\lambda^*_m\geq 0, \tag{16}$$

which leads to $p^*_{mn}\geq\frac{1}{\eta H_m}\left(\sqrt{\frac{(\theta_{mn}+(\theta_{mn}-\theta_{m,n+1})\Lambda_{mn})H_m(1-\eta)}{ac_mH_m+\lambda^*_m/\rho_{mn}}}-1+\eta\right)$.

Substituting (16) into (15c), we have

$$\Bigg(\lambda^*_m-\Bigg(\frac{(\theta_{mn}+(\theta_{mn}-\theta_{m,n+1})\Lambda_{mn})H_m(1-\eta)}{(\eta H_m p^*_{mn}+1-\eta)^2} - ac_mH_m\Bigg)\rho_{mn}\Bigg)p^*_{mn}=0, \tag{17}$$

which leads to two possible values of the optimal solutions $p^*_{mn}=0$ or

$$p^*_{mn}=\frac{1}{\eta H_m}\Bigg(\sqrt{\frac{(\theta_{mn}+(\theta_{mn}-\theta_{m,n+1})\Lambda_{mn})H_m(1-\eta)}{ac_mH_m+\lambda^*_m/\rho_{mn}}} - 1+\eta\Bigg). \tag{18}$$

Considering the constraint $p_{mn}>0$ in (10), which is also the reason for introducing the Lagrange multipliers $\mathbf{U}$, we know that if the value of (18) is negative, we only have to choose the solution $p^*_{mn}=0$. Thus, we summarize the following two cases to choose each p^*_{mn} specifically.

Case 1: If λ^*_m satisfies $\frac{(\theta_{mn}+(\theta_{mn}-\theta_{m,n+1})\Lambda_{mn})H_m}{ac_mH_m+\lambda^*_m/\rho_{mn}}>1-\eta$, then we have

$$p^*_{mn}=\frac{1}{\eta H_m}\Bigg(\sqrt{\frac{(\theta_{mn}+(\theta_{mn}-\theta_{m,n+1})\Lambda_{mn})H_m(1-\eta)}{ac_mH_m+\lambda^*_m/\rho_{mn}}} - 1+\eta\Bigg). \tag{19}$$

Case 2: If λ^*_m satisfies $\frac{(\theta_{mn}+(\theta_{mn}-\theta_{m,n+1})\Lambda_{mn})H_m}{ac_mH_m+\lambda^*_m/\rho_{mn}}\leq 1-\eta$, then the value of p^*_{mn} in (18) is negative, thus we have to choose $p^*_{mn}=0$.

Step 4: Obtain $\mathbf{P}^*$ by the closed-form solution

Without loss of generality, we initiate $\mathbf{L}=\mathbf{0}$. According to Step 3, we can get each initial element of $\mathbf{P}$ in different cases. If there are BBU groups satisfying $\sum_{n=1}^{N}p_{mn}<1$, we define the collection of those BBU groups as $\mathbf{b}$ and accept the corresponding allocated fractions as the optimal fractions $\{p^*_{mn},m\in\mathbf{b};n=1,\cdots,N\}$. In these BBU groups, the InP still has idle BBU resources after allocation.

For any BBU group $m\notin\mathbf{b}$, we assume that the InP leases all the BBU resources out, leading to $\sum\limits_{n=1}^{N}p_{mn}=\sum\limits_{n=1}^{N}\frac{1}{\eta H_m}\left(\sqrt{\frac{(\theta_{mn}+(\theta_{mn}-\theta_{m,n+1})\Lambda_{mn})H_m(1-\eta)}{ac_mH_m+\lambda^*_m/\rho_{mn}}}-1+\eta\right)=1$, which can be used to solve $\{\lambda^*_m,m\notin\mathbf{b}\}$. Then, we can return to Step 4 to get $\{p^*_{mn},m\notin\mathbf{b},n=1,\cdots,N\}$.

Following $\{p^*_{mn},m\in\mathbf{b}\}$ and $\{p^*_{mn},m\notin\mathbf{b}\}$, we can get every optimal element of $\mathbf{P}$, which results in $\mathbf{P}^*$. Then, we use (11) to get the price matrix $\mathbf{E}^*$. Thus, we obtain the optimal contract.

We outline the steps to solve (10) in Algorithm 1, which are similar to the steps to solve (27) presented in Section 5 except for some minor differences. For example, equation (22) under complete information is given by

$$p^*_{mn}=\frac{1}{\eta H_m}\left(\sqrt{\frac{\theta_{mn}H_m(1-\eta)}{ac_mH_m+\lambda^*_m/\rho_{mn}}}-1+\eta\right)>0. \tag{20}$$

We note that in Algorithm 1 we do not consider the monotonicity constraint in (10), since monotonicity constraints hardly appear in the traditional convex

Algorithm 1 Convex Optimization Algorithm

Input: η, β, s_0, k_m, H_m, θ_{mn}, ρ_{mn}, $m = 1, 2, \cdots, M; n = 1, 2, \cdots, N$.

Output: Optimal allocation fraction matrix $\mathbf{P}^*$ and price matrix $\mathbf{E}^*$.

Steps:

1: Obtain the dual problem of (10) by the Lagrangian function

$$\min_{\mathbf{U},\mathbf{L}} \quad \mathrm{Z}(\mathbf{P}, \mathbf{U}, \mathbf{L}) \quad \text{s.t.} \quad \mathbf{U} \geq \mathbf{0}, \ \mathbf{L} \geq \mathbf{0}. \tag{21}$$

2: Write the KKT conditions satisfied by the unique solution $(\mathbf{P}^*, \mathbf{U}^*, \mathbf{L}^*)$ and simplify them

3: Based on the simplification, obtain the closed-form solution
if λ_m^* satisfies $\frac{(\theta_{mn}+(\theta_{mn}-\theta_{m,n+1})\Lambda_{mn})H_m}{ac_m H_m+\lambda_m^*/\rho_{mn}} > 1-\eta$, **then**

$$p_{mn}^* = \frac{1}{\eta H_m}\left(\sqrt{\frac{(\theta_{mn} + (\theta_{mn} - \theta_{m,n+1})\Lambda_{mn})H_m\,(1-\eta)}{ac_m H_m + \lambda_m^*/\rho_{mn}}} - 1 + \eta\right) > 0. \tag{22}$$

else $p_{mn}^* = 0$.
end if

4: Initiate $\mathbf{L} = \mathbf{0}$ and solve initiated $\mathbf{P}$ by the closed-form solution

5: **If** BBU group m satisfying $\sum_{n=1}^{N} p_{mn} < 1$, **then** accept the corresponding allocated fractions as the optimal fractions $\{p_{mn}^*, m \in \mathbf{b}; n = 1, \cdots, N\}$.
else for BBU group $m \notin \mathbf{b}$, solve $\{\lambda_m^*, m \notin \mathbf{b}\}$ by using

$$\sum_{n=1}^{N} p_{mn} = \sum_{n=1}^{N} \frac{1}{\eta H_m} \left(\sqrt{\frac{(\theta_{mn} + (\theta_{mn} - \theta_{m,n+1})\Lambda_{mn})H_m\,(1-\eta)}{ac_m H_m + \lambda_m^*/\rho_{mn}}} -1 + \eta\right) = 1. \tag{23}$$

after getting those positive λ_m^*, return to Step 3 to get the rest of optimal allocated fractions $\{p_{mn}^*, m \notin \mathbf{b}; n = 1, \cdots, N\}$.
end if

6: Combining $\{p_{mn}^*, m \in \mathbf{b}; n = 1, \cdots, N\}$ and $\{p_{mn}^*, m \notin \mathbf{b}; n = 1, \cdots, N\}$, we have $\mathbf{P}^*$. Then, use (11) to get the corresponding $\mathbf{E}^*$.

optimization problem. As such, the solution achieved by Algorithm 1 may not guarantee the monotonicity constraint. Therefore, we next propose an algorithm named “Recurrent Bunching and Ironing” to adjust the solution achieved by Algorithm 1, in order to guarantee the monotonicity constraint, and get the optimal solution to the problem in (10). A similar algorithm has been proposed in [30], but it cannot be used here since the optimal problem in [30] has no constraint. Before detailing the “Recurrent Bunching and Ironing” algorithm, we first present the following lemma to confirm the optimality of the achieved solution by this algorithm.

***Lemma** 4:* We suppose that $\mathbf{x}^\dagger$ can maximize $F(\mathbf{x})$, which is given by

$$\mathbf{x}^\dagger = \arg\max_{\mathbf{x}} F(\mathbf{x}) = \arg\max_{\mathbf{x}} \sum_{i=1}^{I} f_i(x_i), \quad \text{s.t.} \quad \sum_{i=1}^{I} x_i \leq 1, \tag{24}$$

where $F(\mathbf{x}) = \sum_{i=1}^{I} f_i(x_i)$ is a concave function of $\mathbf{x}$, $\mathbf{x} = [x_1, x_2, \cdots, x_I]$, and $f_i(x_i)$ is a concave function of x_i. We arrange $x_i^\dagger$ in an order $x_1^\dagger \leq \cdots \leq x_j^\dagger$, $x_{j+1}^\dagger > \cdots > x_{j+K}^\dagger$, $x_{j+K+1}^\dagger \leq \cdots \leq x_I^\dagger$, where $j \in \{1, 2, \cdots, I-K\}$ and $K = 1, 2, \cdots, I-1$. Then, the optimal $\mathbf{x}$ that maximizes $F(\mathbf{x})$ subject to $x_1 \leq \cdots \leq x_i \leq \cdots \leq x_I$, which is mathematically given by

$$\mathbf{x}^* = \arg\max_{\mathbf{x}} F(\mathbf{x}), \quad \text{s.t.} \quad x_1 \leq \cdots \leq x_i \leq \cdots \leq x_I, \ \sum_{i=1}^{I} x_i \leq 1, \tag{25}$$

can be obtained through the following two steps based on $\mathbf{x}^\dagger$ given in (24):

- Step 1: Obtain $\mathbf{x}^\ddagger = [x_{j+1}^\ddagger, \cdots, x_{j+K}^\ddagger]$, which is given by $x_{j+1}^\ddagger = \cdots = x_{j+K}^\ddagger = \arg\max_{x} \sum_{k=1}^{K} f_{j+k}(x)$.
- Step 2: If $\sum_{k=1}^{K} x_{j+k}^\ddagger \geq \sum_{k=1}^{K} x_{j+k}^\dagger$, update $\mathbf{x}^\dagger$ by setting $x_{j+1}^\dagger = \cdots = x_{j+K}^\dagger = 1/K \sum_{k=j+1}^{K} x_{j+k}^\dagger$ and then obtain $\mathbf{x}^*$ as $\mathbf{x}^* = \mathbf{x}^\dagger$. Otherwise, update $\mathbf{x}^\dagger$ by setting $x_{j+1}^\dagger = \cdots = x_{j+K}^\dagger = \arg\max_{x} \sum_{k=1}^{K} f_{j+k}(x)$ and then obtain $\mathbf{x}^*$ as $\mathbf{x}^* = \mathbf{x}^\dagger$.

Proof: The detailed proof is presented in Appendix D.

We note that in the obtained BBU allocation fraction matrix $\mathbf{P}^*$ from the convex optimization algorithm detailed in Algorithm 1, we may have multiple subsequences in which the monotonicity constraint of p_{mn}^* cannot be guaranteed. As such, following Lemma 4, we detail the “Recurrent Bunching and Ironing” algorithm in Algorithm 2.

We now briefly clarify how to solve the optimization problem in (10) by using Algorithm 1 and Algorithm 2. Since we assume that $\theta_{m1} \leq \cdots \leq \theta_{mN}$, we should check whether the achieved $\mathbf{P}^*$ by the convex optimization algorithm detailed in Algorithm 1 can guarantee the monotonicity constraint, i.e., $p_{m1} \leq \cdots \leq p_{mN}$ for $m = 1, \cdots, M$. If the monotonicity constraint cannot be guaranteed, the “Recurrent Bunching and Ironing” algorithm detailed in Algorithm 2 will be applied to adjust the solutions (i.e., elements of $\mathbf{P}^*$). Based on Lemma 4, the optimality of the adjusted $\mathbf{P}^*$ can still be guaranteed.

Algorithm 2 Recurrent Bunching and Ironing Algorithm

Input: Allocation fraction matrix $\mathbf{P}^*$ obtained by Algorithm 1.
Output: Allocation fraction matrix $\widehat{\mathbf{P}}$ under monotonicity constraint.
Steps:

1: **while** find a decreasing sub-sequence $p^*_{m,r} \geq p^*_{m,r+1} \geq \cdots \geq p^*_{m,r+k}$ **do**
2: Initiate $\widehat{\mathbf{P}} = \mathbf{P}^* = \arg\max_{\mathbf{P}} \overline{U}_I$ and calculate $P = \sum_{i=0}^{k} \hat{p}_{m,r+i}$
3: set $\hat{p}_{m,r} = \cdots = \hat{p}_{m,r+k} = \arg\max_{p} \sum_{n=r}^{r+k} \big(B_O(\theta_{mn}, p) - C(p)\big)\rho_{mn}$
4: **If** $\sum_{i=0}^{k} \hat{p}_{m,r+i} \geq P$ **then** set $\hat{p}_{m,r+i} = \frac{1}{k+1}P$ for $\forall i = 0, 1, \cdots, k$
5: **else** accept $\{\hat{p}_{m,r+i}, i = 0, 1, \cdots, k\}$
6: **end if**
7: **end while**

5 Comparison: Complete Information Case

In this section, we present contract design with complete information [39] as a benchmark, where the InP has perfect information on θ_{mn}. Also this complete information case can be used for performance comparison.

Actually, whether the InP can obtain the perfect information is depending on different scenarios. Some scenarios, the information can be easily obtained. Some other scenarios, only asymmetric information can be obtained, which was discussed in the previous section. If the former, then the InP only has to make the contracts acceptable to MNOs. This means that, the designed contracts only need to ensure that the utility achieved by each MNO equals to its reservation utility, which is the least utility each MNO can accept to participate in the trade. In this work, we set the reservation utility for each MNO as zero. Therefore, with complete Information, the InP can achieve the maximal utility by extracting each MNO's surplus as much as possible. Here, the MNO's surplus is the utility more than its reservation utility.

5.1 Optimization Problem and Its Simplification

In this section, we still consider the discrete uniformly distributed θ_m, where θ_{mn} is given by (4). We note that θ_{mn} is exactly known by the InP in the contract design with complete information, which leads to the fact that we do not need to let MNOs report their θ_{mn} and use extra constraints to guarantee the truth of the reported θ_{mn}. Then, the optimization problem at the InP for the contract design with complete information can be written as

$$\max_{\mathbf{P},\mathbf{E}} \quad U_I \tag{26a}$$
$$\text{s.t.} \quad B_O\left(\theta_{mn}, p_{mn}\right) - \varepsilon_{mn} = 0, \tag{26b}$$
$$\sum_{n=1}^{N} p_{mn} \leq 1, \ 0 \leq p_{mn} \leq 1, \tag{26c}$$

where the constraint (26b) guarantees that the utility of each MNO in the m-th BBU group is equal to its reservation utility, which makes the contract acceptable.

To solve the optimization problem in (26), we first rewrite the objective function in (5) subject to the constraint given in (26b) as $\widetilde{U}_I = \sum_{m=1}^{M} \sum_{n=1}^{N} \big(B_O(\theta_{mn}, p_{mn}) - C(p_{mn})\big)\rho_{mn}$, which is achieved by substituting (26b) into (5). We note that (26b) determines the one-to-one relationship between the BBU allocation fraction matrix $\mathbf{P}$ and the corresponding price matrix $\mathbf{E}$. As such, the corresponding optimization problem at the InP can be rewritten as

$$\max_{\mathbf{P}} \ \widetilde{U}_I \tag{27}$$
$$\text{s.t.} \ \sum_{n=1}^{N} p_{mn} \leq 1, \quad 0 \leq p_{mn} \leq 1, \quad m = 1, 2, \cdots, M,$$

where the InP only has to determine $\mathbf{P}$.

5.2 Solution to the Optimization Problem

To solve the optimization problem given in (27), we can first prove that $\widetilde{U}_I$ is a concave function of $\mathbf{P}$ for any given $m \in \{1, 2, \cdots, M\}, n \in \{1, 2, \cdots, N\}$, which is similar to the proof of Lemma 3. Then, we can adopt the convex optimization techniques to solve (27), which is similar to Algorithm 1.

6 Numerical Results

In this section, we present numerical results of the optimal contract designs with complete and asymmetric information, based on which the impact of some system parameters on the BBU allocation is examined and many useful insights are provided accordingly. Without other statements, we set the ratio of the BBU operating cost to the power consumption as $a = 2/1000$ US$/W, the reference BBU speed as $s_0 = 1$ GHz, and the exponential coefficient of BBU speed as $\beta = 2$ [33, 37, 38]. In the following numerical results, we consider four cases with different system settings, which are detailed in Table 1.

TABLE 1
Four cases with different system settings.

Cases	Scenario	M	N
Case 1.1	Asymmetric	$M = 1$	$N = 3$
Case 1.2	Complete	$M = 1$	$N = 3$
Case 2.1	Asymmetric	$M = 2$	$N = 3$
Case 2.2	Complete	$M = 2$	$N = 3$

6.1 BBU Allocation in Homogeneous Networks

We first consider the BBU resource allocation in homogeneous wireless networks, where there is only one BBU group. Specifically, we mainly examine the BBU resource allocation in Case 1.1 and Case 1.2.

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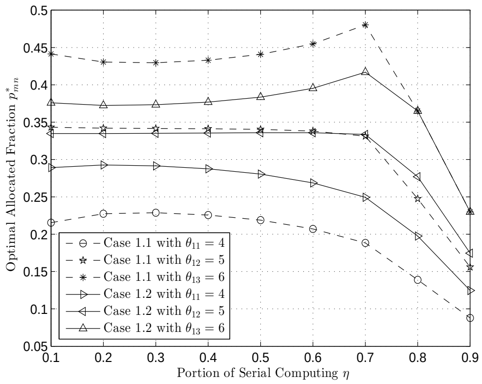

Fig. 2. Optimal BBU allocation fraction p^*_{mn} versus η, where $M = 1$, $k_1 = 5$, $H_1 = 100$, $\theta_{11} = 4$, $\theta_{12} = 5$, and $\theta_{13} = 6$.

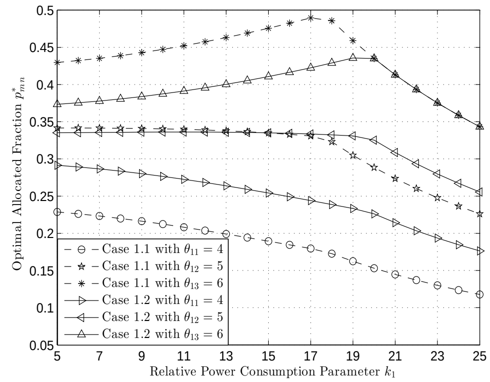

Fig. 3. Optimal BBU allocation fraction p^*_{mn} versus k_1, where $M = 1$, $\eta = 0.3$, $H_1 = 100$, $\theta_{11} = 4$, $\theta_{12} = 5$, and $\theta_{13} = 6$.

In Fig. 2, we examine the effect of the parallel parameter η on the optimal contract design. We note that η is proportional to the serial task at each MNO. As a result, when η is small, MNO can use the parallel computing method to process tasks, thus achieving a higher benefit by renting more BBU resources. In this figure, comparing the curves for Case 1.1 and Case 1.2, we can see that the InP optimally allocates more BBU resources to the MNO with the highest θ_{mn} and allocates fewer BBU resources to the MNO with the lowest θ_{mn} in the contract designed with asymmetric information relative to the contract designed with complete information. This is due to the fact that without the complete information the InP can potentially obtain more profit by allocating more BBUs to the more important clients, i.e., the MNOs with higher θ_{mn}. In Fig. 2, we also observe that when $\eta < 0.3$, the BBU resources allocated to the MNOs with relatively high θ_{mn} decrease with η, while that allocated to the MNOs with relatively low θ_{mn} increase with η. This is due to the fact that when η is relatively small, every MNO tends to obtain more benefits by renting more BBUs. However, the BBU resources are limited and the MNOs with relatively high θ_{mn} are more important to the InP, and thus the InP will first meet the demand of these MNOs. Surprisingly, when η is between 0.3 and 0.7, we observe that the BBU resources allocated to the MNOs with relatively high θ_{mn} increase with η, while that allocated to the MNOs with relatively low θ_{mn} decrease with η. This is due to the fact that the increase in η leads to more reduction in the benefit of the MNO with a higher θ_{mn} according to (2) and for some specific values of η (i.e., $0.3 < \eta < 0.7$) the MNO may need to rent more BBUs to counteract this reduction. In addition, as we show in this figure, the sum of ρ_{mn} will be less than 1 when η is large enough, i.e., $\eta > 0.7$, which means the BBU resources may be abundant for a relatively large η. This is due to the fact that the benefit MNO can obtain from parallel computing is minor when η is large and thus it is not cost-effective for MNO to rent BBUs as much as it can. Finally, in this figure we observe that p^*_{mn} monotonically increases with θ_{mn}, which confirms the monotonicity of the optimal BBU allocation fraction with respect to θ_{mn} and can be explained by our Lemma 1. Intuitively, this is reasonable since the InP can potentially achieve more benefit from the MNOs with high θ_{mn}, while the cost of operating the BBUs is independent of the MNOs.

In Fig. 3, we investigate the effect of the relative power consumption parameter k_1(W/GHz) on the optimal contract design. Based on the discussion below (1), we note that a larger k_1 indicates a larger power consumption but also a higher processing ability, i.e., different values of k_1 represent different groups of BBUs. In this figure, we first observe that when k_1 is small. $k_1 < 17$ for Case 1.1 and $k_1 < 19$ for Case 1.2, the BBU resources allocated to the MNOs with relatively high θ_{mn} increase with k_1, while that allocated to the MNOs with relatively low θ_{mn} decrease with k_1. This is due to the fact that under the specific system settings (e.g., $\beta = 2$) the increase in k_1 leads to a larger increase in the power consumption than that in the processing ability, since we assume that the power consumption is $c_m = (\frac{k_m s_0}{\theta_{mn}})^\beta$ and the BBU processing ability is $k_m s_0$, which means that the BBUs become more precious as k_1 increases and the InP will allocate more of them to the clients of more importance to potentially gain more profit. However, when k_1 is large. $k_1 > 17$ for Case 1.1 and $k_1 > 19$ for Case 1.2, further increase in k_1 means that the BBUs are too expensive to use by the InP or to rent by the MNOs. As such, in this figure we observe that the allocated BBU resources to all the MNOs decrease with k_1 when k_1 is relatively large and the sum of ρ_{mn} is less than one.

Following Fig. 3, we present Fig. 4 to show the effect of the relative power consumption parameter k_1 on the InP's total utility. In this figure, we first observe that the InP's maximum utility decreases visibly with k_1 in Case 1.1, while in Case 1.2 this utility occurs no reduction as k_1 increases. This is due to the fact that as k_1 increases, the cost $C(p_{mn})$ increases in both Case 1.1 and Case 1.2. However, because of the perfect information InP can obtain in Case 1.2, it can maintain its utility by raising the price ε_{mn}. In addition, the InP's maximum utility achieved with complete information in Case 1.2 is always higher than that achieved with

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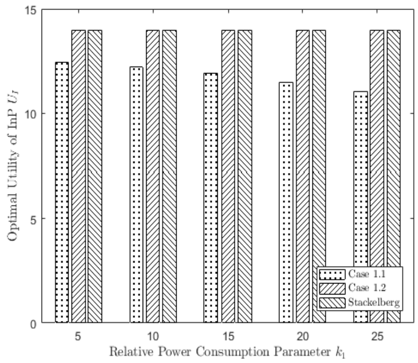

Fig. 4. InP's optimal utility U_I versus k_1 in Case 2.1, Case 2.2 and Stackelberg game theoretic approach, where $M=1$, $\eta=0.3$, $H_1=100$, $\theta_{11}=4$, $\theta_{12}=5$, and $\theta_{13}=6$.

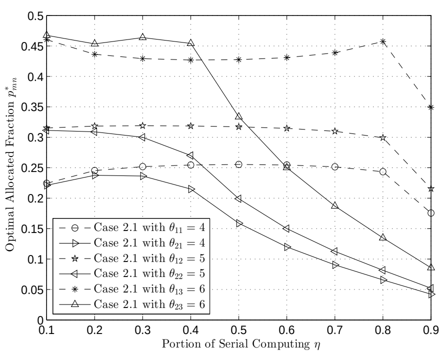

Fig. 5. Optimal allocation fraction p^*_{mn} versus η, where $\beta=2$, $M=2$, $k_1=5$, $k_2=20$, $H_1=H_2=50$, $\theta_{11}=\theta_{21}=4, \theta_{12}=\theta_{22}=5, \theta_{13}=\theta_{23}=6$.

complete information in Case 1.1, which is due to the fact that the InP can guarantee the zero utility at each MNO when it has accurate information of the MNO type. The utility reduction in Case 1.1 relative to Case 1.2 is the cost of missing the accurate information on θ_{mn}. Fig. 4 also demonstrates that this reduction monotonically increases with k_1, which is due to the fact that a larger k_1 means that the BBU resources are more precious for higher processing ability and higher cost $C(p_{mn})$, and thus missing the accurate information on θ_{mn} leads to more waste in the BBU allocation.

6.2 Heterogeneous BBUs Allocation

In this subsection, we discuss the BBU allocation in heterogeneous wireless networks, where there are multiple BBU groups. Specifically, we mainly examine the BBU allocation in two different cases, i.e., Case 2.1 and Case 2.2, which are detailed in Table 1.

In Fig. 5, we investigate the effect of the parallel parameter η on the optimal contract design with asymmetric information, i.e., Case 2.1. In this figure, with the growth of η, the changing trend of allocated BBU resources with $k_1=5$ is similar to Case 1.1 in Fig. 2, while the allocated BBU resources with $k_2=20$ always decrease. The reason is that, when the relative power consumption parameter is small, the influence of higher processing ability is more significant. However, if the parameter is large, the influence of larger power consumption is more significant.

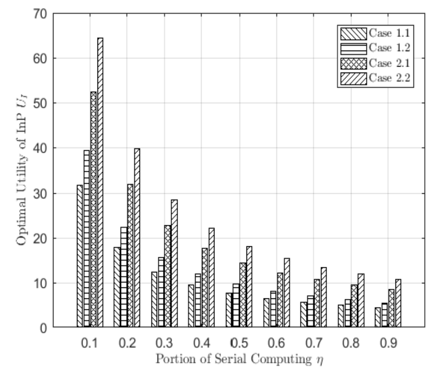

Fig. 6. InP's optimal utility versus η. In Case 1.1 and Case 1.2, $M=1$, $k_1=5$, $H_1=100$, $\theta_{11}=4$, $\theta_{12}=5$, $\theta_{13}=6$. In Case 2.1 and Case 2.2, $M=2$, $k_1=5$, $k_2=20$, $H_1=H_2=50$, $\theta_{11}=\theta_{21}=4$, $\theta_{12}=\theta_{22}=5$, $\theta_{13}=\theta_{23}=6$.

In Fig. 6, we present the maximum utility achieved by the InP with different values of η in the considered four cases as detailed in Table 1. In this figure, we first observe that for the same amount of BBUs, the maximum utility achieved by the InP in heterogeneous networks with multiple BBU groups is higher than that achieved in homogeneous networks with a single BBU group. This is due to the fact that the InP can allocate BBUs from different groups to different MNOs when the InP has multiple BBU groups, which offers more flexibility to the InP and potentially can bring in more profit. Thus, allocating heterogeneous BBUs is more profitable and realistic for the InP. In addition, although having heterogeneous BBUs can increase InP's utility relative to having the same amount of homogeneous BBUs, the examination also demonstrates that, in order to obtain the true preference of MNOs, the InP has to sacrifice some utility, and this sacrificed utility at the InP is higher for heterogeneous BBUs than that for homogeneous BBUs. In this figure, we also observe that the InP's maximum utility decreases with η. This is due to the fact that when η is larger, the benefit MNO can obtain from parallel computing is less, then MNO will reduce the number of rented BBUs. Finally, in this figure we observe that the extra utility achieved by the InP with complete information relative to that achieved with asymmetric information (i.e., the extra utility achieved in Case 1.2 relative to Case 1.1 and extra utility achieved in Case 2.2 relative to Case 2.1) decreases with η. This is due to the fact that when η is large, the optimal solutions to p_{mn} with the complete information and with the asymmetric information are similar, since $\theta_{mn}H_m\left(1-\eta\right)$ in (20) is close to $(\theta_{mn}+(\theta_{mn}-\theta_{m,n+1})\Lambda_{mn})H_m\left(1-\eta\right)$ in (22).

In Fig. 7, we examine the effect of the MNO type parameter θ_{mn} on each MNO's utility in the contract design with asymmetric information (i.e., Case 1.1 and Case 2.1). We note that in these cases each MNO's utility is ensured to be zero. In this figure, we first observe that

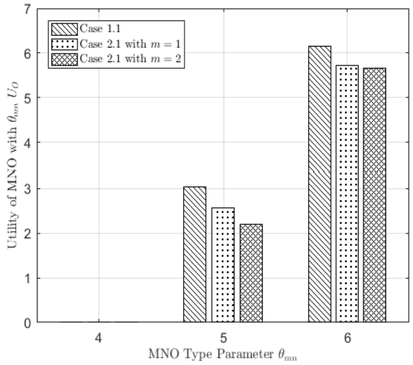

Fig. 7. MNO's utility versus θ_{mn}. In Case 1.1, $M = 1$, $\eta = 0.3$, $k_1 = 5$, $H_1 = 100$, $\theta_{11} = 4$, $\theta_{12} = 5$, $\theta_{13} = 6$. In Case 2.1, $M = 2$, $\eta = 0.3$, $k_1 = 5$, $k_2 = 25$, $H_1 = H_2 = 50$, $\theta_{11} = \theta_{21} = 4, \theta_{12} = \theta_{22} = 5, \theta_{13} = \theta_{23} = 6$.

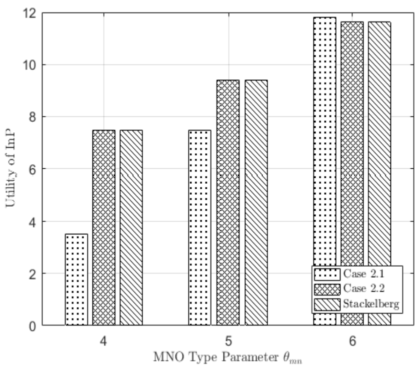

Fig. 8. InP's utility versus θ_{mn}. In Case 2.1, Case 2.2 and Stackelberg game theoretic approach, $M = 2$, $\eta = 0.3$, $k_1 = 5$, $k_2 = 20$, $H_1 = H_2 = 50$, $\theta_{11} = \theta_{21} = 4, \theta_{12} = \theta_{22} = 5, \theta_{13} = \theta_{23} = 6$.

the utility of the MNO achieved from the BBU group with the lowest θ_{mn} is zero, which can be explained by our Lemma 2. This observation demonstrates that, in order to let all MNOs accept the contracts designed for them and achieve the maximal utility, the InP will make the utility of MNO with lowest θ_{mn} equal to its reservation utility (i.e., zero utility). We also observe that the utility gained by the MNO monotonically increases with θ_{mn}. This is due to the fact that the MNO with a larger θ_{mn} is more important to the InP and thus the InP will leave it with more surplus in order to attract it to accept the designed contract. Finally, in this figure we observe that the utility achieved by the MNO from the BBUs with $k_1 = 5$ is higher than that achieved from the BBUs with $k_2 = 20$. Considering the observations in Fig. 5, this indicates that the InP prefers to use the BBUs that offer lower utilities to the MNO, i.e., larger utilities to the InP.

In Fig. 8, we examine the effect of θ_{mn} on the InP's utility achieved by allocating BBUs from different groups to different MNOs (corresponding to different values of θ_{mn}). In this figure, we first observe that the InP's utility extracted from each MNO increases with θ_{mn} in the contract designs with complete and asymmetric information, which confirms that the MNO with a higher θ_{mn} is more important to the InP in terms of providing more profit. In addition, the InP's utility extracted from MNO with the highest θ_{mn} in the designed contract with asymmetric information is even higher than that in the designed contract with complete information, which is consistent with the discussion on Fig. 2 that without complete information the InP can obtain more profit by allocating more BBUs to the clients of more importance.

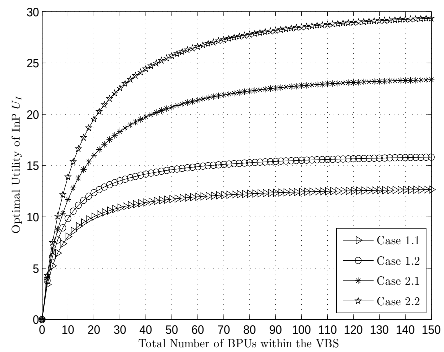

Fig. 9. InP's optimal utility versus total number of BBUs within the VBS. In Case 1.1 and Case 1.2, $M = 1$, $k_1 = 5$, $\eta = 0.3$, $\theta_{11} = 4$, $\theta_{12} = 5$, $\theta_{13} = 6$. In Case 2.1 and Case 2.2, the number of BBUs within each group is even, $M = 2$, $k_1 = 5$, $k_2 = 20$, $\eta = 0.3$, $\theta_{11} = \theta_{21} = 4, \theta_{12} = \theta_{22} = 5, \theta_{13} = \theta_{23} = 6$.

In Fig. 9, we examine the impact of the total number of BBUs within the VBS on the InP's maximum utility under the considered four different system settings, where we equalize the total number of BBUs between the two BBU groups in Case 2.1 and Case 2.2. In this figure, we first observe that the InP's maximum utility increases approximately logarithmically with the total number of BBUs, which indicates that a small number of BBUs can enable the InP to achieve the most utility. This is due to the fact that the InP will not allocate all the BBUs to the MNOs when the total number of BBUs is sufficiently large and the InP's maximum utility is not limited by this total number. Our examination can aid to determine the total number of BBUs in the implementation of practical C-RANs. Specifically, we can first observe that there exists a utility upper limit for each case. Corresponding to the upper limit, we can obtain the maximum required number of the BBUs in each case, e.g., Case 2.2 requires the largest number of BBUs while Case 1.1 requires the smallest number of BBUs. It indicates that the complete and heterogeneous case requires more BBUs than the asymmetric and homogeneous case. This is due to the fact that InP will not worry wasting of BBU resources when it has complete information and InP has more flexibility to allocate the BBUs in heterogeneous case.

6.3 Performance Comparison

To the authors' knowledge, there are quite a few methods that can be adopted to solve the heterogeneous BBU resource allocation problem, especially when the information is asymmetric. In order to compare performances of the incentive mechanism we proposed with other methods, we regard Stackelberg game theoretic approach as a comparison [29]. In the Stackelberg game, a leader (i.e. the InP) takes actions to maximize his utility, while followers (i.e. MNOs) adjust actions to maximize their own utilities after observing the leader's actions. We explicit its results in Fig. 4 and 8. We can find that, the Stackberg game theoretic approach is equivalent to the contract theoretic approach under information complete case. The reason is that, Stackberg game theoretic approach can not involve statistical information about MNOs. Thus, it is no need to consider the reliability of provided information, and is same as the problem described under information complete case. However, it is unpractical to obtain complete information for the InP. Thus, the proposed incentive mechanism is more realistic.

7 Conclusion

In this paper, we proposed an incentive mechanism based on contract theory to allocate heterogeneous BBU resources in cellular networks, where the InP has to provide a set of quality-price contract items to the MNOs in order to obtain the maximal utility. The contract was designed to effectively stimulate each MNO to accept the contract item that is deliberately designed for it. We explicitly presented the algorithms to determine the optimal contract designs with complete and asymmetric information available to the MNOs. With asymmetric information, two extra constraints (i.e., IC and IR constraints) should be satisfied in order to ensure the MNOs to accept the designed contracts, relative to the case with complete information. The provided solutions showed that the utility at all the MNOs were guaranteed to their reservation utility under the complete information case, while only the utility at the MNO with the lowest type was guaranteed to its reservation utility under the asymmetric information case. Simulation results showed that, comparing with the optimal contracts with complete and asymmetric information on the MNOs, the information asymmetry in heterogeneous BBU resources allocation led to a higher utility reduction of the InP. It is also noted that heterogeneous BBUs can bring a higher utility to the InP than homogeneous BBUs since the InP has more flexibility to allocate BBUs from different groups to different MNOs and can potentially bring in more profit with the heterogeneity of computing resources in C-RANs. We also examined the sufficient number of BBUs in wireless networks and showed that this number is larger for heterogeneous BBUs relative to homogeneous BBUs.

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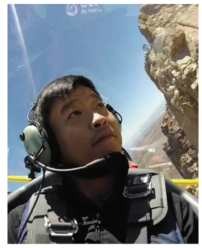

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